Predicting and Classifying Cognitive and Psychological Traits Using Computational Multiplex Networks

Research Thesis

In Partial Fulfillment of The Requirements for the Degree of Master of Science in Behavioral and Management Sciences – Cognitive Psychology and Human Factors Engineering

Gal Samuel

Submitted to the Senate of the

Technion – Israel Institute of Technology

Elul, 5782, Haifa, September 2022

The Research thesis was done under the supervision of

Dr. Yoed N. Kenett

in the Faculty of Industrial Engineering and Management.

The generous financial help of the Technion – Israel Institute of Technology is gratefully acknowledged

Publications of this work

Experiment 1 was presented in the following virtual conferences:

Poster - Gal Samuel, Massimo Stella, Roger E. Beaty & Yoed N. Kenett (2022). Predicting Openness to Experience via a Multiplex Cognitive Network Approach. The 9th Israeli Conference on Cognition Research (ISCOP 2022).

Talk - Gal Samuel, Massimo Stella, Roger E. Beaty & Yoed N. Kenett (2021). Predicting Openness to Experience via a Multiplex Cognitive Network Approach. Complexity and Cognition (CompCog), Conference on Complex Systems (CCS2021).

Experiment 1 is also under review for publication:

Gal Samuel, Massimo Stella, Roger E. Beaty & Yoed N. Kenett (Under Review). Predicting Openness to Experience via a Cognitive Multiplex Network and Machine Learning. Journal of Research in Personality.

Table of Contents

List of Figures and Tables

Abstract

Creativity is a multidimensional, complex concept, that is composed of various cognitive processes, and therefore, quite difficult to research. Creative thinking helps us identify and solve problems, and be innovative, which is why it is important for us as a society to know more about it. Research of creativity has highlighted how semantic memory is an important component of creativity because it facilitates linking remote concepts together, in order to create new and original ideas. Lately, there has been a surge in the use of computational methods in order to study the role of memory in creative thinking. However, only a few attempts have been made to study more complex structures of knowledge that include multiple dimensions, and their relation to creativity. In this thesis, I apply computational methods to study a multidimensional representation of the mental lexicon, and how the way people search through it in a mental navigation task predicts creative thinking and the personality trait Openness to Experience. This, via a multiplex network analysis, which allows representing complex systems as a multidimensional graph. Results from two experiments show individual differences in the way people navigate their multidimensional mental lexicon. These differences serve in predicting creativity and Openness to Experience scores. In Experiment 1, a classifier of low- and high- Openness to Experience individuals showed an accuracy of 75%. In Experiment 2, such a classification was further improved to 91%, and prediction of individuals scores was $r(479) = .69$, MSE = 0.1, $p < .001$. Experiment 2 also included a prediction and classification of two different types of creativity scores, one, measured with a self-report questionnaire (ICAA) and another measured with a divergent thinking task (AUT). ICAA's best classification was 82% and prediction was $r(479) = 0.47$, MSE = 2454.74 , $p < .001$. AUT best classification was 62% and prediction was $r(479) = .17$, MSE = 0.002 , $p < .001$. Although AUT scores classification and prediction were lower compared to

Openness and ICAA, it still performed above chance level of classification and a significant relation between predicted and actual scores was found. Taken together, the results of Experiments 1 and 2 provide an exciting proof for the ability to use computational tools such as multiplex networks, to study and predict complex cognitive traits.

Introduction

Creativity is defined as the generation of novel and useful ideas (Runco & Jaeger, 2012), related to a search process that “moves away" from common ideas (Kenett, 2018). The creative process relies on ones’ semantic memory structure and executive processes that guide such searches (Benedek & Neubauer, 2013; Kenett et al., 2016; Kenett & Faust, 2019; Mednick, 1962; Beaty et al., 2014; Volle, 2018). The merging of remote, weakly related concepts into a novel and applicable concept defines the creative process, as described by the associative theory of creativity (Mednick, 1962). This theory was in the past challenging to directly examine, given the difficulty of studying mental representations such as those stored in semantic memory.

Creativity and Semantic Memory Networks

Recent computational advances have paved the way to computationally study semantic memory structure and processes that operate over it. One such approach that has been gaining popularity is cognitive network science (Baronchelli et al., 2013; Borge-Holthoefer & Arenas, 2010; Castro & Siew, 2020; Hills & Kenett, 2022; Karuza et al., 2016; Siew et al., 2019). Cognitive network science applies computational network science methodologies, that are based on mathematical graph theory. These computational tools have been applied to study broad cognitive domains, such as language, memory, learning, aging, and creativity (Kenett & Hills, 2022; Siew et al., 2019).

However, current cognitive network science research largely studies single types of networks, e.g., semantic networks or phonological networks. Yet, the mental lexicon is considered to be a multidimensional structure with different layers, that reflect different types of features (e.g., phonology, semantics, etc.). Thus, studying multidimensional, or multilayer, cognitive networks is needed to advance our understanding of the complexity of the human mind (Hills & Kenett, 2022). In fact, research using a more complex multidimensional cognitive structure, recently demonstrated its ability to classify lower- and higher- creative individuals, based on a simple semantic fluency task (Stella & Kenett, 2019).

Cognitive Multiplex Networks

To achieve such a creativity classification, the authors used a complex structure called ‘multiplex network’, to represent lexical memory in a broad fashion. A multiplex network is a mathematical structure composed of a number of independent networks, or layers, and the overlapping nodes between them. The multiplex network preserves the links from all independent layers and merges the independent layers into one multiplex network (Castro & Stella, 2019; Stella, 2019; Stella et al., 2018; Stella & Kenett, 2019; Figure 1). In Stella & Kenett (2019), the layers included lexical information, consisting of a synonyms layer, a phonological layer, an associative layer and a hypernym/hyponym layer. Using all these layers together computationally, allowed examining the way people exploit their lexical memory in relation to differences in creative thinking. In addition, this analysis allowed classifying lower- and higher- creative individuals, based on the way these individuals "walked" on the multiplex network (Stella & Kenett, 2019). Importantly, the authors focused on a component called the Largest Viable Cluster (LVC), to measure participants' performance on a verbal fluency task. The LVC is a component of the multiplex network made of the largest collection of nodes which are connected between themselves across all independent layers of the multiplex (Stella et al., 2018; Figure 1). It is composed of highly concrete, familiar words. Moreover, the emergence of it was recently found to be connected to explosive stages of language acquisition (Stella, Beckage, Brede & De Domenico, 2018). In short, Stella & Kenett (2019) found that lower- and higher- creative individuals significantly differentiate in the way they rely on the LVC when generating animal category members, and in the number of responses they can generate.

Figure 1.

Multiplex Network and the Largest Viable Cluster.

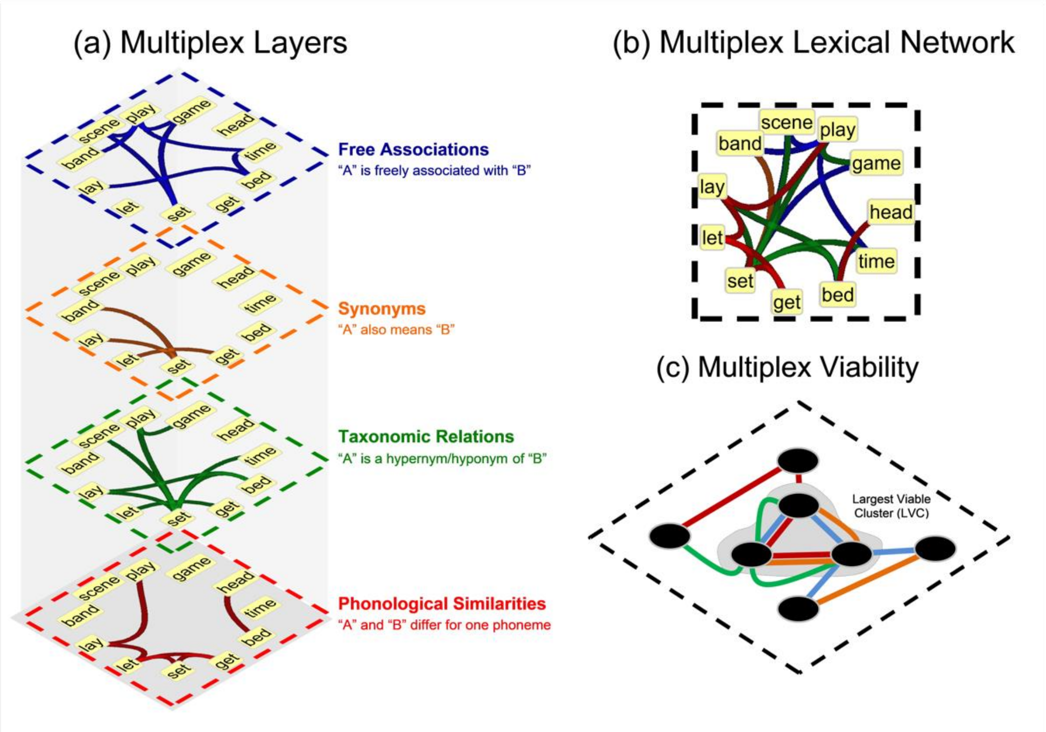


Figure 1. (A) In the multiplex structure, nodes represent concepts replicated across four layers, namely free associations, synonyms, taxonomic relations, and phonological similarities. (B) All layers can be condensed in one edge-colored network, where links of multiple colors co-exist. Each color represents one layer (e.g., red for phonological similarities). (C) In these edge-colored networks, the largest viable cluster (LVC) is the largest set of nodes that are simultaneously connected across all layers. There must always be at least one sequence of links connecting any two nodes in an LVC, for every layer in the network.

Current Study

The study by Stella and Kenett (2019) was largely a proof of concept, analyzing a small dataset to examine the overall success of a cognitive multiplex network to predict such complex behavior. The current study aims to take the next step, replicating and extending this work and attempting to predict creativity scores using a cognitive multiplex network's measures, several other tasks, and a machine learning model. The tasks used in the current study to compute multiplex network measures, are semantic fluency tasks, which consist of an operationalization of participants’ mental navigation over memory. In this task, participants are required to generate as many category members as possible, in one minute. This task was previously shown to be useful when examining how people search through their memory (Abbott et al., 2015; Hills et al., 2012, 2015) and allow us to trace the steps of participants, navigating their mental path on the lexical structure.

In this research I attempted to predict Openness to Experience and creativity scores. This was conducted via a machine learning model, specifically, a supervised learning model. This model used the cognitive multiplex network measures, which were calculated based on each participant’s performance in the semantic fluency task, to predict their target scores. The use of supervised learning models for predictions is a widely popular approach. For example, it is used to predict hospitalization due to heart diseases (Dai et al., 2015), and slope stability (Lin et al., 2018). However, as far as we know, little or no cognitive research has been conducted with similar machine learning approaches.

In Experiment 1, I focused on predicting the personality trait Openness to Experience. Openness to Experience, like creativity, is described as a complex trait, and is specifically known for its relation to creativity (Christensen et al., 2018; Lee & Ashton, 2010). Reanalyzing an existing dataset (Beaty et al., 2018), that included a semantic fluency task, and an Openness to Experience assessment, Experiment 1 aimed to predict Openness to Experience scores and to classify low- and high- Openness participants. The hypothesis was that machine learning models will be able to predict Openness to Experience scores and classify low- and high- Openness to Experience participants.

Following this, similar methods were used in Experiment 2 in order to predict creativity scores. With a much larger dataset, Experiment 2 aimed to replicate and extend Stella & Kenett's results, showing a higher classification rate for low- and high- creative individuals, and to create a successful prediction model for creativity scores. Furthermore, in Experiment 2 with the larger sample size, I attempted to predict Openness to Experience and classify low- and high- Openness individuals and thus extend Experiment 1's results.

Experiment 1

In Experiment 1, I examined whether the personality trait of Openness to Experience can be predicted based on participants' mental navigation on a multiplex cognitive lexicon. To achieve this, I re-analyzed data previously collected by Beaty et al. (2018), who investigated the relation between brain connectivity, and creative thinking. The results of experiment 1 provide further evidence for the relation between the mental lexicon and personality and the ability of machine learning models to predict complex behavior. Moreover, because of the highly researched relation between Openness to Experience and creativity, the results of Experiment 1 gave a hint of a relation between the mental lexicon and creativity, later emphasized in study 2. Also, it provides another evidence of the ability to use multiplex network features in order to predict psychological and cognitive traits (Stella & Kenett, 2019).

Methods

Participants

Data collected by Beaty et al. (2018) was reanalyzed. The total sample consisted of 163 participants recruited from the University of North Carolina at Greensboro (UNCG) and the surrounding community (113 women, mean age = 22.50 years, SD = 5.79) and specifically over-sampled art, music, and science majors to increase the sample's population of creative domains. Participants were recruited as part of a larger study on individual differences in creativity (which involved numerous laboratory and ecological measures and procedures not discussed here) and were paid up to $100 for their time. All participants were right-handed with normal or corrected-to-normal vision and reported no history of neurological disorder, cognitive disability, or medication that affects the central nervous system. Participants provided written informed consent. The study was approved by the UNCG Institutional Review Board (Beaty et al., 2018).

Materials

Behavioral Assessments

Associational fluency (hot synonyms). Participants were required to list (type) as many synonyms to the word *hot* as they could, in one minute. Generated responses that were not synonyms to *hot* were excluded from final analysis. Responses that were not synonyms to *hot* were preprocessed via the SemNA package, including automatic spelling corrections and exclusion of irrelevant responses (Christensen & Kenett, 2021). All the valid responses were saved, and responses were preprocessed to fix typos, nonsensical responses, and remove repetitions, using the SemNA pipeline (Christensen & Kenett, 2021).

Personality assessment. The Big-5 personality traits (and corresponding facets) were assessed using the 240 item NEO-PI-3 questionnaire (McCrae et al., 2005). For the NEO-PI-3 items that measure Openness, the researchers that collected the data preformed confirmatory factor analysis via the Weighted Least Squares Mean and Variance (WSLMV) estimator to estimate factor scores. This analysis was conducted using the *lavaan* package in R (version 0.6.10; Rosseel, 2012); these factors scores were used for subsequent prediction analyses.

Group assignment

Based on Christensen et al. (2018) and in an attempt to replicate Stella and Kenett (2019), we first divide participants into low- and high- Openness classes based on their Openness factor score percentile. The percentile threshold (X), separating across the classes, was fixed through a parameter sweep that examined the difference between the low- and high- groups, using a non-parametric Mann-Whitney U-test, starting with X equal to .025 and proceeding with steps of .025 up until .5. The value of X maximizing these statistics was selected as a candidate for partitioning the data. This value was relative to X = .30, so that the “low” class became the cluster of individuals falling in the lower 30th percentile of the distribution of Openness (N = 46) and the “high” class became the cluster of individuals with the highest 30% of scores in the same distribution (N = 46).

In addition to this “extreme groups” classification analysis, we also conducted a regression analysis with the full sample. Such analysis circumvents issues of splitting individuals who vary on a continuous score into groups and allows us to analyze the full data. Thus, we first follow Stella and Kenett (2019) and conduct a classification analysis. We then extend this line of research by conducting a prediction analysis in relation to the full dataset.

Cognitive multiplex analysis

Multiplex construction. Our multiplex network consisted of four networks, that constituted its layers: Free associations, synonyms, phonological, and hypernyms/hyponyms. To create the cognitive multiplex network, all of the layers were treated as undirected. Data for all layers except for free associations was obtained from WordData repository presented by WolframResearch, Champaign, IL, US, and available through Mathematica 11.3 program. The WordData dataset is based on WordNet 3.0 (Miller, 1995). WordNet 3.0 is a dictionary that includes information about word-word similarities as computed from English dictionaries (Stella et al., 2018). Specifically, the multiplex includes the following four layers:

- **Free associations layer:** created using data of associations elicited by participants, from the Small World of Words project (De Deyne et al., 2019).

Only links that were elicited more than 10 times were considered eligible, for the association layer to feature the same link density of other multiplex layers.

- **Synonym layer:** consists of word-word relations that represent meaning overlapping between the words, such as *hot* and *warm*.
- **Phonological layer:** consists of word-word relations that represent one phoneme difference between words, such as *cat* (kæt) and *bat* (bæt).
- **Hypernyms/Hyponyms layer**: consists of word-word relations that represent generalization and specification, such as *bird* and *eagle*.

Multiplex measures. After creating the multiplex, we computed the Largest Viable Cluster (LVC, see Baxter et al. 2016) which is the largest cluster of words that are connected across all layers. Similar to Stella and Kenett (2019), we compute several cognitive multiplex network measures and use multivariate statistical analyses to determine which variables significantly differ across the groups.

We used the fluency task responses of each participant to identify where the participant "walks" on the network, and compute multiple measures for each participant (Stella & Kenett, 2019; **Table 1**). The measures focus on aspects such as the interaction of each participant with the LVC, the entropy of paths participants used in their mental navigation, the amounts of responses each participant generated in general, within, and outside of the LVC (see **Table 1**).

Table 1

List of multiplex network properties assessed from participants fluency list.

Name	**Definition**
Number of Responses	Number of responses in the list.
Coverage per Response	Average number of visited nodes in the multiplex shortest paths from one response to the next one.
Fraction of responses in LVC	Fraction of words in the list being part of the LVC.
Fraction of LVC Accesses	In the collective walk collating all shortest paths between response$_{_i}$ and response_i+1 for all responses, check how many nodes in the LVC were visited over the total number of visited nodes.
Entropy of LVC Accesses	Always in the collective walk, put a 0 if a visited node is outside of the LVC, put 1 otherwise. On this binary list B, compute the Shannon entropy.
Entropy of LVC Coverage	Entropy of the collective walk w_{iN}, including nodes not in *l* but in the multiplex lexical network and being inside or outside the LVC.
Entropy of LVC Responses	Entropy of nodes inside/outside the LVC as contained in the list *l*.
Maximum Permanence in LVC	Maximum number of visited nodes in the collective walk w_{iN} being consecutively in the LVC.
Median Permanence in LVC	Median number of nodes in all the visits to the LVC during the collective walk w_{iN}.
Accesses to LVC from *hot*	Average number of visited nodes in the LVC in the multiplex shortest path between responses and *hot*.
Max Out	On the binary list above, check the length of the largest block containing all consecutive 0s.
Median Out	On the binary list above, compute the median of the lengths of all blocks containing consecutive 0s.
Distance from *hot* per response	For every response$_{_i}$, measure the shortest path length between response$_{_i}$ and the target category, e.g., *hot*. Sum the lengths and divide them by the number of responses.
Start in the LVC	Flag for the first response being in the LVC.
Fraction of typos	Percentage of incorrect spelling responses.
Norm 1	A normalized version of the maximum permanence in the LVC. Maximum number of visited nodes in the collective walk w_{iN} being consecutively in the LVC, divided by the number of responses.
Norm 2	This is a normalized version of the average permanence in the LVC. Median number of nodes in all the visits to the LVC during the collective walk w_{iN}, divided by the number of responses.

Machine Learning Analysis

Data Splitting. The data for the machine learning model is split into two parts – training data and test data. The data splitting method we used was leave-one-out cross-validation (LOOCV; Alpaydin, 2020), in which all data points except one are used to train the model, and then the trained model is tested on the remaining data point. In this method, the split reoccurs multiple times so that each data point (i.e., the vector of measures relative to individual participants) is used as the test set exactly once. We use LOOCV to account for the contained sample size of this study while maximizing size and variability in the test set, thus reducing overfitting and producing more robust machine learning models (Alpaydin, 2020).

Models. To learn how to classify the data, and how to predict a score, there is a need for a learning model, that is based on a certain method or rule. In our case, we used a binary logistic regression approach for the classification model (Alpaydin, 2020). This method weighs the features' importance in predicting the score for each subject and returns a binary prediction (low- or high- Openness). We used linear regression, which is similar to the binary logistic regression, but returns a continuous score and not a binary one. Linear regression was chosen for the prediction, as it allows us to identify the significance of each feature in predicting the Openness, and to easily compare goodness-of-fit between models, using Pearson's R. Importantly, to find the best regression models, both in prediction and in classification, we followed a stepwise regression model. For classification, a forward stepwise regression was chosen, where features are added to the regression model when significantly improving the model's area under the curve (AUC). For our prediction analysis, we used a backwards stepwise regression, where features are removed from the regression model when its removal significantly improves the model's *p*-value. Importantly, albeit using backwards stepwise regression as the default, the reason we chose to use forward stepwise regression for classification was that backwards regression converged with a minimal dataset of only 36 participants. This meant losing approximately 60% of the sample due to missing values in some of the chosen features. Therefore—to capitalize on the entire dataset and avoid overfitting based on a small sample—we chose to use forward regression instead, which converged leaving more participants in the analysis.

Statistical Analysis

The first step of the analysis was to calculate each of the multiplex measures for each participant, based on their list of *hot* synonyms. Next, we created two groups, consisting of participants with the lowest and highest 30% of Openness scores. Then, a comparison between group scores for each network measure was calculated using a Mann-Whitney U statistical test. In parallel, we conducted a Pearson's R test to measure the correlation between each of the multiplex measures and Openness scores. Finally, two computational analyses were conducted. First, all multiplex measures were used as the basis for a **prediction** model of Openness. Using the LOOCV approach and a backwards stepwise linear regression, a model was fitted to the data. Second, all multiplex measures were again used, this time as the basis for a **classification** model of Openness. A model was created using the LOOCV approach and a backwards stepwise logistic regression.

Model Specificity Analysis

After creating the model based on the Openness scores and finding the features that yield the best result, as a further test of model specificity for predicting Openness, we attempted to predict the other four Big-5 personality traits (Neuroticism, Extraversion, Agreeableness, and Conscientiousness) using the model trained on predicting Openness with the same training set, features, splitting method, and machine learning model. The only difference in this analysis was the test set, which included the additional four Big-5 personality traits. Such an analysis allows us to examine the specificity of our model and how uniquely it relates to Openness.

Results

Low- vs. High- Openness to Experience Group Analysis

We first computed for each participant their cognitive multiplex network properties representing their behavioral performance in the *hot* synonyms task. We then examined the difference between the low- and high- Openness groups across these cognitive multiplex network properties, via a non-parametric Mann-Whitney test.

This analysis revealed significant differences across the two groups in multiple cognitive multiplex network properties, most of which related to the LVC (**Figure 2** and **Table 2**). These properties included the Number of Responses, Coverage per Response, Fraction of Responses in LVC, Entropy of LVC Accesses, Entropy of LVC Responses, Maximum Permanence in LVC, Median Permanence in LVC, Maximum Out, Median Out, Distance from *hot* per Response, and Accesses to LVC from *hot*. Similar to higher creative individuals (Stella & Kenett, 2019), high Openness individuals tended to generate more synonyms to the word *hot*, synonyms that were less related to the LVC.

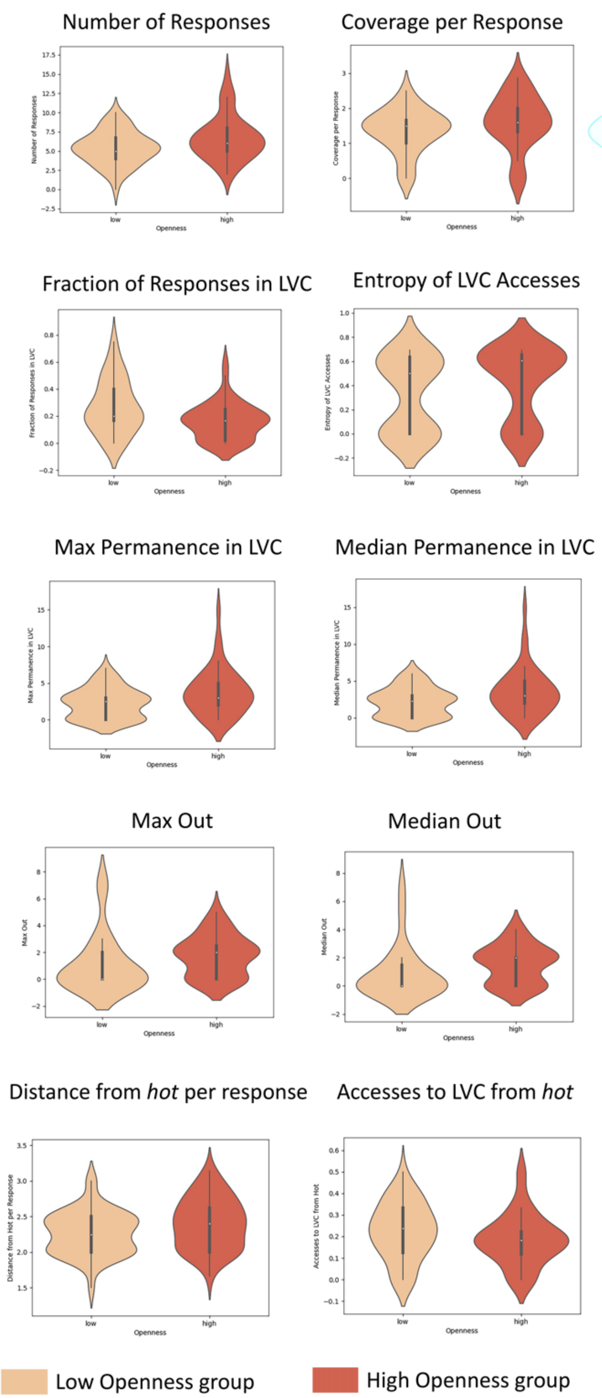
Table 2

Cognitive multiplex network variables that significantly differ between the low- and high- Openness to Experience groups.

Variable	N_{low}	N_{high}	Mann- Whitney U	*p-value*
Number of Responses	46	46	795.50	.019
Coverage per Response	45	45	790.50	.036
Fraction of responses in LVC	45	46	702.50	.004
Entropy of LVC Accesses	45	46	797.50	.027
Maximum Permanence in LVC	46	46	770.00	.011
Median Permanence in LVC	46	46	791.00	.017
Maximum Out	46	46	212.50	.020
Median Out	22	25	180.00	.013
Distance from h*ot* per Response	45	45	806.00	.045
Accesses to LVC from *hot*	45	45	788.00	.035

Figure 2

Violin plots of difference in cognitive multiplex network properties across the low- and high- Openness to Experience groups.



Note - X-axis – the low- and high- Openness groups. Y-axis – the various multiplex network parameters.

Individual Differences Analysis

Next, I examined the relation between the various cognitive multiplex network properties and individual differences in Openness, via Pearson's correlation analysis. This analysis revealed several significant correlations between the various cognitive multiplex network properties and Openness (**Figure 3** and **Table 3**). These properties include: Number of responses, Coverage of response, Fraction of responses in LVC, Entropy of LVC responses, Maximum permanence in LVC, Median permanence in LVC, and Distance from *hot* per response. These significant properties fully correspond with the low- and high- Openness group analysis. These results highlight the general significance of these properties in relation to Openness.

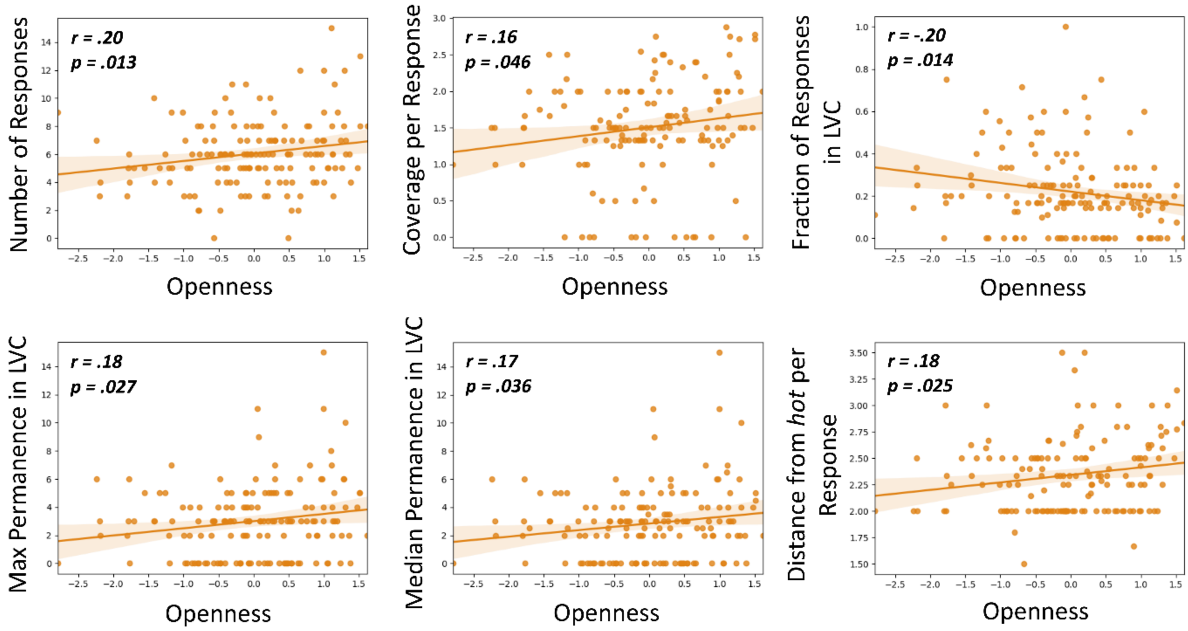
Table 3

Cognitive multiplex network variables that were significantly related to individual differences in Openness to Experience.

Variable	N	***r***	*p*-value
Number of Responses	154	.20	.013
Coverage per Response	148	.16	.046
Fraction of responses in LVC	152	-.20	.014
Maximum Permanence in LVC	154	.18	.027
Median Permanence in LVC	154	.17	.036
Distance from h*ot* per Response	148	.18	.025

Figure 3

Scatter plots of the multiplex network properties across the sample.



Note - Top row from left to right: Number of Responses; Coverage per Response; Fraction of Responses in LVC; Bottom row from left to right: Maximum Permanence in LVC; Median Permanence in LVC; Distance from *hot* per Response. X-axis – Openness to Experience scores, Y-axis - the various multiplex network parameters. Lighter orange background indicates confidence intervals.

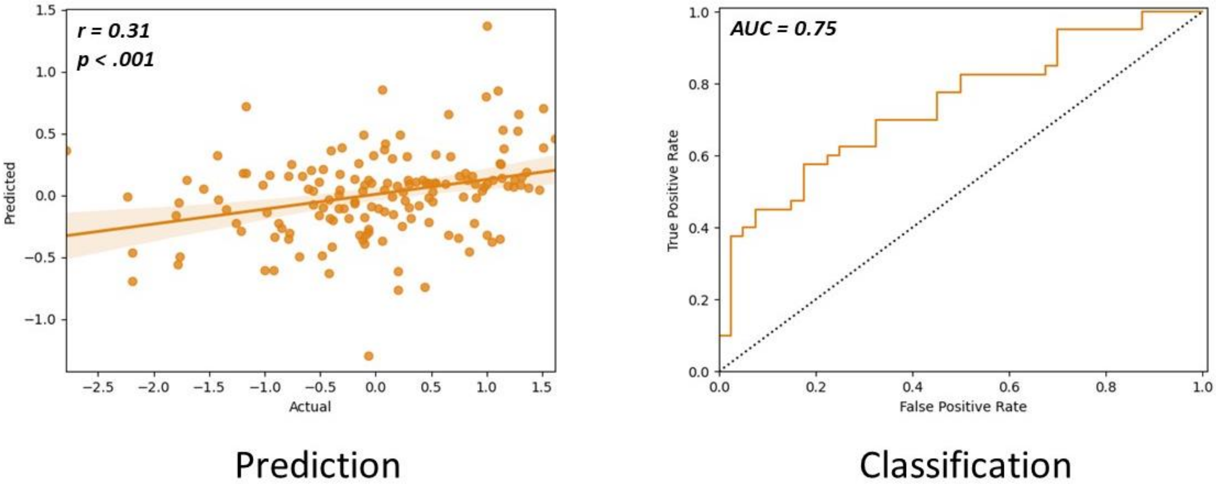
Machine Learning Analysis

As a next step, we examine the performance of our machine learning model to predict and classify Openness (**Figure 4**). The prediction model, using a leave one out cross-validation splitting technique and a backwards stepwise linear regression, yielded a significant correlation between the predicted and actual score, $r(151) = .31$, MSE = 0.74, $p < .001$ using the features Fraction of Responses in LVC, Entropy of LVC Accesses, Max Permanence in LVC, Norm1. The classification model, using a leave one out cross-validation and a logistic regression classifier, yielded an AUC of

.75 using the features Fraction of Responses in LVC, Entropy of LVC Accesses, Fraction of LVC Accesses, Median Permanence in LVC, Entropy of LVC Responses, Fraction of Incorrect Spellings.

Figure 4

Machine learning model results.



Note. Prediction: Correlation between predicted and actual Openness scores. Classification: Receiver operating characteristics (ROC) curve for the classification of low- and high- Openness scores.

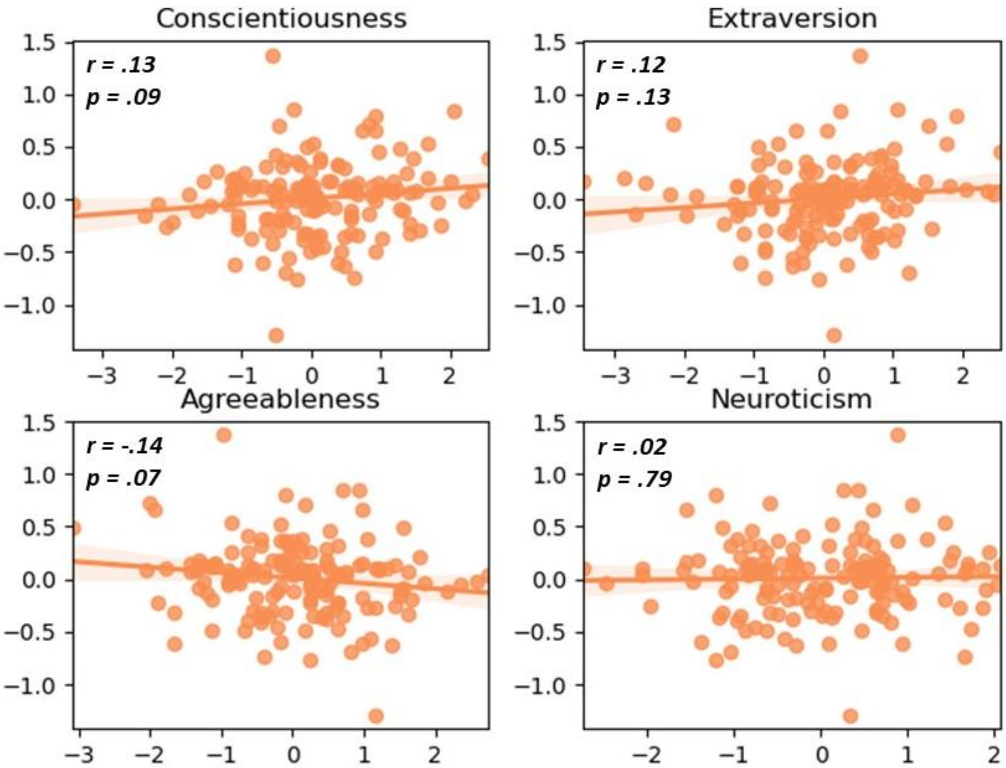
Specificity Analysis

Finally, we examined the specificity of our model for predicting Openness, and not any other personality trait. We do so by testing the success of this trained model in capturing the additional four personality traits from the Big-5 model. As expected, our prediction model—using leave one out cross-validation splitting and a backwards stepwise linear regression, and trained on the Openness data—yielded nonsignificant correlations between predicted scores and actual scores with the additional four personality traits (**Figure 5**): Conscientiousness, $r(151) = .13$, MSE = 1.01, $p = .09$; Extraversion, $r(151) = .12$, MSE = 1.05, $p = .13$; Agreeableness, $r(151) = -.14$, MSE =

1.22, p = .07; and Neuroticism, *r(151)* = .02, MSE = 1.07, p = .79. These results indicate that the model trained on Openness scores is unable to provide meaningful predictions for the additional four personality traits, providing evidence of its specificity in predicting Openness.

Figure 5

Results of prediction of the Big-5 personality traits other than Openness, using the model trained to predict Openness.



***Note* -** X-axes – Predicted scores. Y-axes – Actual scores.

Discussion

In Experiment 1 I found, differences in how low- and high- Openness to Experience groups rely on the LVC in retrieving synonyms to the word *hot*. Furthermore, a machine learning model was able to predict Openness to Experience scores across individuals. This prediction is based on how participants access and exploit connections in the core LVC of the mental lexicon during their task. Classification model was able to differentiate low- and high- Openness individuals in 75% of the cases. Thus, this experiment shows evidence that personality can be predicted with multiplex network measures, and these results were expected to be improved with a larger sample size in Experiment 2.

Experiment 2

In Experiment 2, I aimed to replicate and extend past findings (Stella & Kenett, 2019) that showed a relation between the mental lexicon and creativity, and that low- and high- creative individuals can be classified with multiplex network features. However, these past findings are based on data collected from 182 participants. In Experiment 2 I use a much larger dataset of 479 participants. Based on the larger dataset and Experiment 1's results, I expect to be able to replicate and extend the findings of Stella and Kenett (2019). Specifically, I expect to be able to replicate the differences in how low- and high- creativity and Openness to Experience groups rely on the LVC in retrieving category-member words in a semantic fluency task, and to achieve an improved prediction and classification rates (Stella & Kenett, 2019).

One difference from Experiment 1 is that in Experiment 2 I will use two different semantic fluency tasks. This, to be able to capture participants' mental navigation's properties as accurately as possible. For this aim, in the prediction and classification models, only the replies to one of these tasks will be used to calculate features, which allows comparing the models.

Moreover, in Experiment 2 I use three different predicted variables: Openness to Experience measured by NEO-PI 3; Inventory of Creative Achievements and Activities (ICAA) score which measures reported creativity; and the Alternative Uses Test (AUT) score, which measures divergent thinking. The first predicted variable aims to replicate Experiment 1, the second and third predicted variables are creativity-adjacent measures.

Methods

Participants. Four hundred and seventy-nine participants (242 female, 5 participants did not specify; mean age = 37.15 years, SD = 11.23) from predominantly Englishspeaking countries were recruited from the Prolific Academic subjects' pool. They were compensated accordingly and signed a consent form. Only participants who failed more than one of the four attention questions and participants that did not fill the entire survey were disqualified.

Materials.

Semantic Fluency

Semantic verbal fluency (*hot* synonyms). All participants completed the semantic fluency task, with synonyms to the word *hot*, same as in Experiment 1.

Semantic verbal fluency (Animal names). All participants completed the animal category semantic verbal fluency task. According to standard procedure (Ardila et al., 2007), participants had two minutes to generate as many animal category members they could think of. For each participant, repetitions and non-category members were excluded from final analysis.

Creativity Assessments

Inventory of Creative Achievements and Activities (ICAA). ICAA is a questionnaire assessing individual differences in real-life creativity. It measures the frequency of engagement in everyday creative activities and creative achievements in 8 different domains (e.g., arts, writing, cooking, etc.; Diedrich et al., 2018). For each participant, numeral responses from all domains were summed to compute score.

Alternative Uses Task. The alternative uses task was used as another measure of creativity and thinking processes. In this task, participants are presented with an object and are then required to think of as many uses for the object as they can (Acar & Runco, 2019). It consisted of 3 items – broom, belt, and pencil – and each participant performs the task on all the objects, in a randomized order. AUT scores for each participant were computed using the Maximum Associative Distance (MAD; Yu et al., 2022). This method takes each reply, and of it, retrieves the word that is maximally remote from the object that was given in the AUT to assess originality. After performing this, we averaged each participant's replies scores to get their general AUT score.

Forward Flow

Forward flow. The forward flow task from Gray et al. (2019), which provides a way to empirically measure how one searches through their memory was used. Participants complete three trials, using the same starting words from Gray and colleagues: table, bear, and candle. For each trial, participants are shown one of the starting words and are asked to "write down (type) the next word that follows in your mind from the previous word." They are instructed to only type single words, and not to type proper nouns (such as names, brands, etc.), which are not commonly included in text corpora used to compute forward flow. Each trial presents a starting word followed by 19 text boxes, where participants type their chained free association responses. To calculate Forward Flow score, we used multiple semantic spaces and combined them into a latent factor score. For more information about this method (Beaty et al., 2021).

Intelligence

Intelligence Assessment. Participants completed a couple of intelligence tasks commonly used in past work on intelligence and creativity (Beaty & Silvia, 2012; Frith et al., 2021; Kenett et al., 2016b). The tasks assessed fluid intelligence (*Gf*) and included: 1) a number series task (15 items, 5 minutes), which presents sequences of numbers that change based on a rule and asks participants to select the next sequence (Thurstone, 1938) and 2) a series completion task from the Culture Fair Intelligence Test (13 items, 3 minutes), which presents sequences of three changing images (small line drawings) and asks participants to select the next image that fits the rule governing their change (Cattell & Cattell, 1961/2008). Finally, participants' scores were the average amount of correct responses ratio of the two tasks.

Personality

Personality traits. All participants completed a personality assessment using NEO-PI-3 (McCrae et al., 2010), same as in Experiment 1.

Curiosity

Curiosity. Participants completed a 22-items 5-point Likert-scale questionnaire that assesses various aspects of curiosity. These 22 items were identified and selected from existing questionnaires (Five-Dimensional Curiosity - social curiosity, Workplace Curiosity - organizational curiosity, I/D-type Curiosity -intellectual cognition and information seeking and Perceptual Curiosity - specific configuration and diverse configuration) in previous experiment (Kashdan et al., 2020; Collins, Litman & Spielberger, 2004; Litman, 2008; Litman & Jimerson, 2004; Litman & Spielberger, 2003; Litman & Spielberger, 2003). Finally, responses were averaged to compute curiosity score.

Group assignment

Multiplex analysis was conducted similarly to the analysis conducted in Experiment 1, however, in Experiment 2 there were three different dependent variables, as opposed to only one in Experiment 1. Therefore, to complete the low- vs. high- group assignment and comparison, three different analyses were made. One based on Openness to Experience scores, another based on the ICAA scores and third based on the AUT scores. Three pairs of groups were made based on lowest and highest 30% dependent variables' participants. Each analysis groups' demographics were computed (**Table 4**).

Table 4

Assigned groups' demographics in Experiment 2.

Dependent Variable	Low/High Group Size (total)	Female (Male)*	Age (SD)
Openness to Experience	143 (286)	142 (141)	37.07 (11.00)
AUT	143 (286)	148 (135)	36.44 (11.33)
ICAA	143 (286)	131 (151)	32.93 (11.28)

* Some participants did not specify gender.

Cognitive multiplex analysis

Multiplex analysis was conducted twice, once for each semantic verbal fluency task responses (synonyms to hot; animals), similarly to the analysis conducted in Experiment 1.

Machine learning analysis

Machine learning analysis was conducted similarly to the analysis conducted in Experiment 1. It was conducted for each of the target scores, using the Semantic verbal fluency responses. It was also conducted once for each semantic verbal fluency task responses. Therefore, for each target score (ICAA/AUT/Openness) there were 2 sets of predictors (animal names/hot synonyms w/ behavioral tasks) and two models (classification with logistic regression/prediction with linear regression) – 3x2x2 analyses.

Statistical analysis

Statistical analysis was conducted similarly to the analysis conducted in Experiment 1, for all three targets, with both sets of semantic fluency replies.

Procedure. All participants filled an approximately one-hour long online questionnaire on Qualtrics, which included four attention checks. All participants completed all tasks. The order of the tasks was randomized across participants.

Results

Openness to Experience as dependent variable

Low- vs. High- Openness to Experience Group Analysis

I first computed for each participant their cognitive multiplex network properties representing their behavioral performance in both semantic fluency tasks and their scores in the behavioral tasks. I then examined the difference between the low- and high- Openness groups across these cognitive multiplex network properties, via a non-parametric Mann-Whitney test.

This analysis revealed significant differences across the two groups in multiple measures, many of which related to the LVC (**Table 5**).

Table 5

Variables that significantly differ between the low- and high- Openness to Experience groups.

	Variable	N_{low}	N_{high}	Mann-Whitney U	*p-value*
Animal category members	Number of Responses	143	143	7545	< .001
	Coverage per Response	143	142	8803	.026
	Fraction of Responses in LVC	143	143	8636	.011
	Entropy of LVC Responses	143	143	8697.5	.014
	Median Out	116	116	5889.5	.039
	Distance from Animal per Response	143	142	8474	.007
	Entropy of Access to LVC	143	143	7940.5	< .001
	Norm1	143	143	8945.5	.033
hot synonyms	Fraction of Responses in LVC	143	143	7945.5	< .001
	Fraction of LVC Accesses	140	140	8636	.042
	Entropy of LVC Responses	143	143	8278.5	.002
Behavioral tasks	AUT score	143	143	8010	< .001
	Curiosity	143	143	2762	< .001
	ICAA score	143	143	4087	< .001
	Extraversion	143	143	8265	.002
	Agreeableness	143	143	6600	< .001
	Forward Flow	113	126	6058	.023
	Intelligence	143	143	8364.5	.003

Individual Differences Analysis

Next, I examined the relation between various cognitive multiplex network properties and other behavioral variables, and individual differences in Openness, via Pearson's correlation analysis. This analysis revealed several significant correlations between the various cognitive multiplex network properties and Openness (**Table 6**).

Table 6

Variables that were significantly related to individual differences in Openness to Experience.

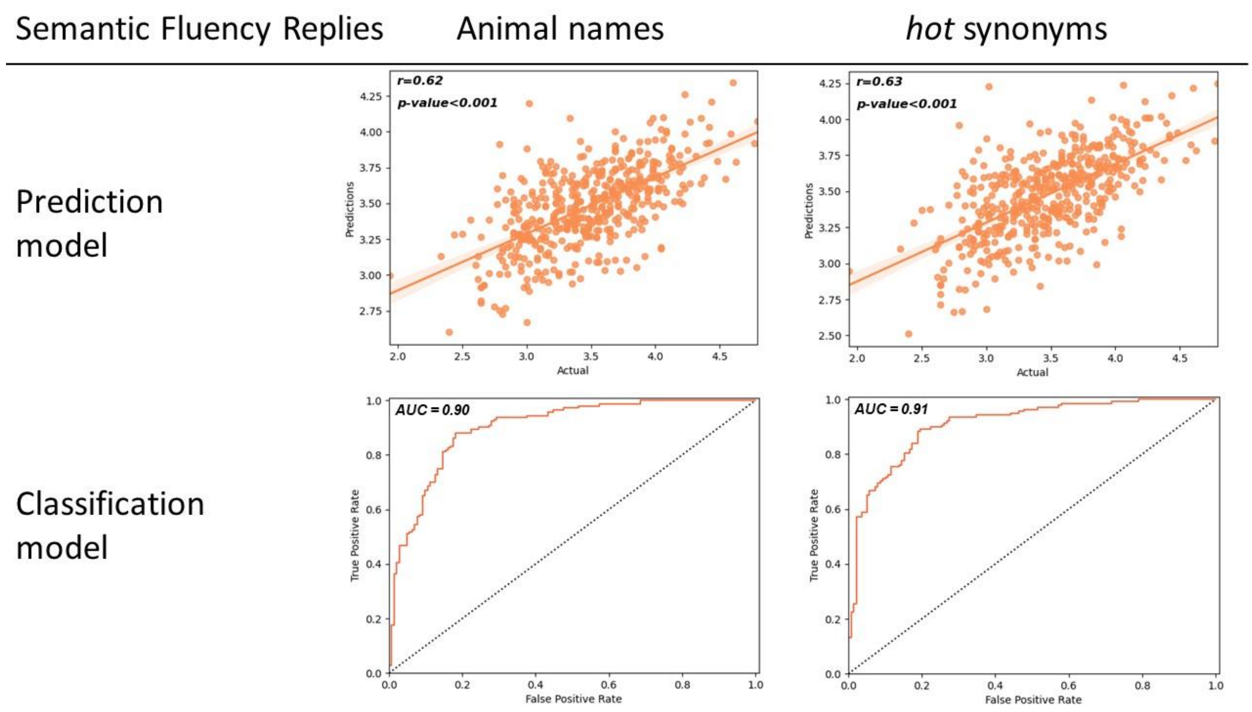
	Variable	N	Pearson's *r*	*p-value*
Animal	Number of Responses	479	0.18	< .001
	Fraction of Responses in LVC	479	-0.13	.005
	Entropy of LVC Responses	479	-0.09	.049
	Median Out	393	-0.12	.018
	Distance from Animal per Response	478	0.12	.007
	Entropy of Access to LVC	479	0.14	.002
hot	Fraction of Responses in LVC	479	-0.16	< .001
	Fraction of LVC Accesses	470	-0.10	.028
	Entropy of LVC Responses	479	-0.10	.034
	Accesses to LVC from Hot	477	-0.10	.027
Behavioral	AUT score	479	0.14	.002
	Curiosity	479	0.61	< .001
	ICAA score	479	0.43	< .001
	Extraversion	479	0.21	< .001
	Agreeableness	479	0.27	< .001
	Forward Flow	407	0.12	.013
	Intelligence	479	0.12	.011

Machine Learning Analysis

As a next step, I examined the performance of the machine learning model to predict and classify Openness (**Figure 6**). The prediction model, using a leave one out cross-validation splitting technique and a backwards stepwise linear regression, yielded a significant correlation between the predicted and actual score. When using the multiplex features that were computed with animal category members semantic fluency task replies, prediction success was $r(479)$ = .68, MSE = 0.11, p < .001 using the features Number of Responses, Curiosity, Neuroticism, Agreeableness, Conscientiousness, Forward Flow. Using the multiplex features that were computed with *hot* synonyms semantic fluency task replies, prediction success was $r(479)$ = .69, MSE = 0.10, p < .001 using the features Fraction of Responses in LVC, Fraction of LVC Accesses, Entropy of LVC Accesses, Max Permanence in LVC, Median Permanence in LVC, Curiosity, Neuroticism, Agreeableness, Conscientiousness. The classification model, using a leave one out cross-validation and a logistic regression classifier with animal names yielded an AUC of .90 using the features Number of Responses, Max Permanence in LVC, Median Permanence in LVC, Entropy of Access to LVC, Start in LVC, Norm1, Curiosity, Neuroticism, Extraversion, Agreeableness, Intelligence, and with *hot* synonyms yielded an AUC of .91 using the features Number of Responses, Coverage per Response, Fraction of Responses in LVC, Fraction of LVC Accesses, Entropy of LVC Accesses, Entropy of LVC Responses, Max Permanence in LVC, Entropy of Access to LVC, Norm2, Curiosity , Neuroticism, Agreeableness, Intelligence.

Figure 6

Machine learning model results.



Note - Upper row, Prediction models, shows correlation between predicted (y-axis) and actual (x-axis) Openness scores. Lower row, Classification model, shows receiver operating characteristics (ROC) curve for the classification of low- and high- Openness scores. Left, using replies from the Animal names semantic fluency task and other behavioral tasks. Right, using replies from the *hot* synonym semantic fluency task and other behavioral tasks.

AUT score as dependent variable

Low- vs. High- AUT Group Analysis

Next, I examined the difference between the low- and high- AUT groups, based on *group assignment* mentioned before, across these cognitive multiplex network properties, via a non-parametric Mann-Whitney test.

This analysis revealed significant differences across the two groups in multiple measures, most of which related to the LVC (**Table 7**).

Table 7

Variables that significantly differ between the low- and high- AUT scores groups.

	Variable	N_{low}	N_{high}	Mann-Whitney U	*p-value*
Animal category members	Fraction of Responses in LVC	143	143	8504	.006
	Entropy of LVC Responses	143	143	8555	.008
	Max Permanence in LVC	143	143	8959	.032
	Start in LVC	143	143	9223.5	.043
hot synonyms	Fraction of Responses in LVC	143	143	8869	.026
	Entropy of LVC Responses	143	143	9061.5	.048
	Median Permanence in LVC	143	143	8961	.034
	Accesses to LVC from Hot	142	143	8960.5	.043
	Start in LVC	143	143	9223.5	.043
	Norm1	143	143	8216.5	.002
	Norm2	143	143	8384	.004
Behavioral tasks	Extraversion	143	143	8717.5	.015
	Openness to Experience	143	143	8194	.001

Individual Differences Analysis

Next, we examined the relation between various cognitive multiplex network properties and other behavioral variables, and individual differences in AUT scores, via Pearson's correlation analysis. This analysis revealed several significant correlations between the various cognitive multiplex network properties and AUT scores (**Table 8**).

Table 8

Variables that were significantly related to individual differences in AUT score.

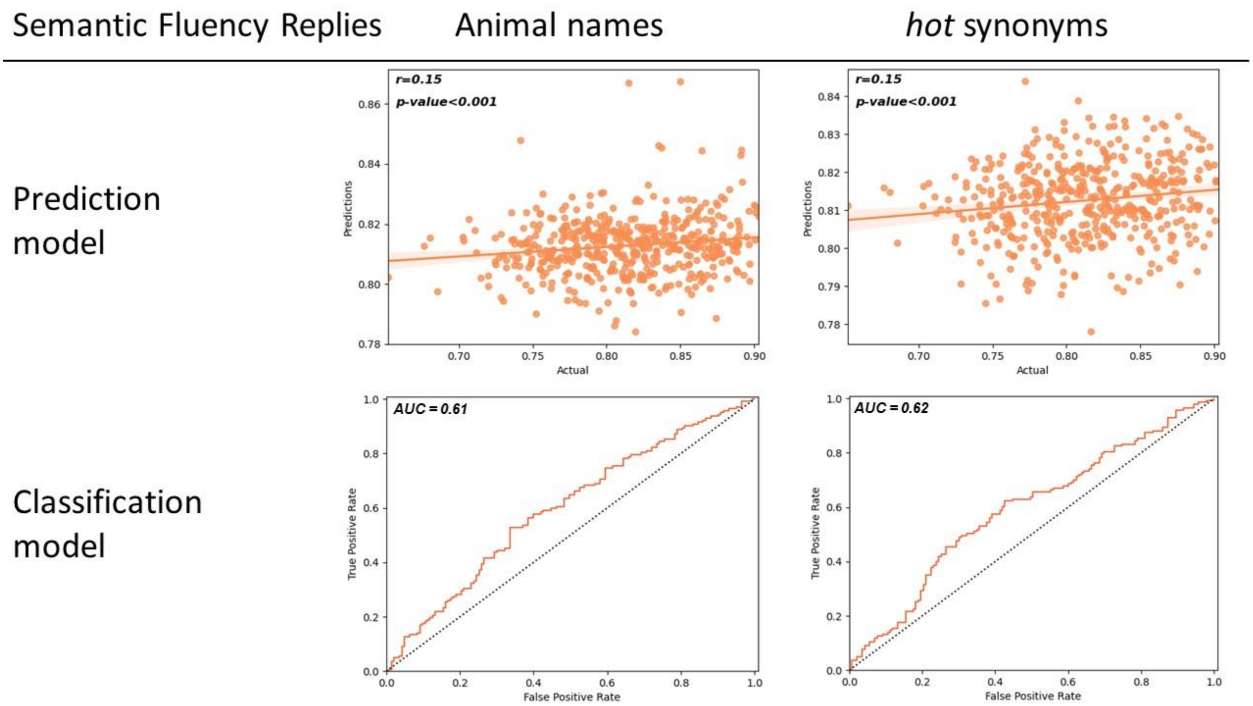
	Variable	N	Pearson's *r*	*p-value*
Animal	Fraction of Responses in LVC	479	-0.13	.003
	Entropy of LVC Responses	479	-0.13	.005
hot	Fraction of Responses in LVC	479	-0.11	.015
	Fraction of LVC Accesses	470	-0.10	.029
	Entropy of LVC Responses	479	-0.10	.028
	Max Permanence in LVC	479	0.10	.022
	Accesses to LVC from Hot	477	-0.11	.019
	Norm1	479	0.14	.001
	Norm2	479	0.11	.019
Behavioral	Openness to Experience	479	0.14	.002

Machine Learning Analysis

As a next step, we examine the performance of our machine learning model to predict and classify AUT scores (**Figure 7**). The prediction model, using a leave one out cross-validation splitting technique and a backwards stepwise linear regression, yielded a significant correlation between the predicted and actual score. When using the multiplex features that were computed with animal category members semantic fluency task replies, prediction success was $r(479) = .17$, MSE = 0.002 , $p < .001$ features used were Fraction of Responses in LVC, Fraction of LVC Accesses, Entropy of Access to LVC, Extraversion, Intelligence. Using the multiplex features that were computed with *hot* synonyms semantic fluency task replies, prediction success was $r(479) = .15$, MSE = 0.002, $p < .001$ features used were Entropy of LVC Accesses, Entropy of LVC Responses, Start in LVC, Norm1, Intelligence. The classification model, using a leave one out cross-validation and a logistic regression classifier with animal names yielded an AUC of .61 with the features Fraction of Responses in LVC, Entropy of LVC Responses, Max Permanence in LVC, Extraversion, Forward Flow, and with *hot* synonyms yielded an AUC of .62 with the features Norm1, Extraversion, Forward Flow.

Figure 7

Machine learning model results.



Note - Upper row, Prediction models, shows correlation between predicted (y-axis) and actual (x-axis) AUT scores. Lower row, Classification model, shows receiver operating characteristics (ROC) curve for the classification of low- and high- AUT scores. Left, using replies from the Animal names semantic fluency task and other behavioral tasks. Right, using replies from the *hot* synonym semantic fluency task and other behavioral tasks.

ICAA score as dependent variable

Low- vs. High- ICAA Group Analysis

We examined the difference between the low- and high- ICAA groups, based on *group assignment* mentioned before, across these cognitive multiplex network properties, via a non-parametric Mann-Whitney test.

This analysis revealed significant differences across the two groups in multiple measures, many of which related to the LVC (**Table 9**).

Table 9

Variables that significantly differ between the low- and high- ICAA score groups.

	Variable	N_{low}	N_{high}	Mann-Whitney U	*p-value*
Animal category members	Number of Responses	143	143	6770.5	< .001
	Coverage per Response	143	143	7576	< .001
	Fraction of Responses in LVC	143	143	8203	.002
	Fraction of LVC Accesses	143	143	8573	.009
	Entropy of LVC Accesses	137	139	8196	.022
	Entropy of LVC Responses	143	143	8477	.006
	Distance from Animal per Response	143	143	8044.5	< .001
	Accesses to LVC from Animal	143	143	8709	.015
	Entropy of Access to LVC	143	143	7750.5	< .001
	Norm1	143	143	8504.5	.006
	Norm2	143	143	7923.5	< .001
hot synonyms	Number of Responses	143	143	8197	.001
	Fraction of Responses in LVC	143	143	8567.5	.008
	Entropy of LVC Responses	143	143	8820.5	.022
	Accesses to LVC from Hot	143	142	8977	.045
	Number of Responses	143	143	8197	.001
	Fraction of Responses in LVC	143	143	8567.5	.008
Behavioral tasks	Curiosity	143	143	4218	< .001
	Neuroticism	143	143	9027.5	.043
	Extraversion	143	143	8633	.011
	Openness to Experience	143	143	3777	< .001
	Conscientiousness	143	143	8491.5	.007
	Forward Flow	110	124	5328	.002
	Intelligence	143	143	8699.5	.014

Individual Differences Analysis

Next, we examined the relation between various cognitive multiplex network properties and other behavioral variables, and individual differences in ICAA scores, via Pearson's correlation analysis. This analysis revealed several significant correlations between the various variables and ICAA scores (**Table 10**).

Table 10

Variables that were significantly related to individual differences in ICAA scores.

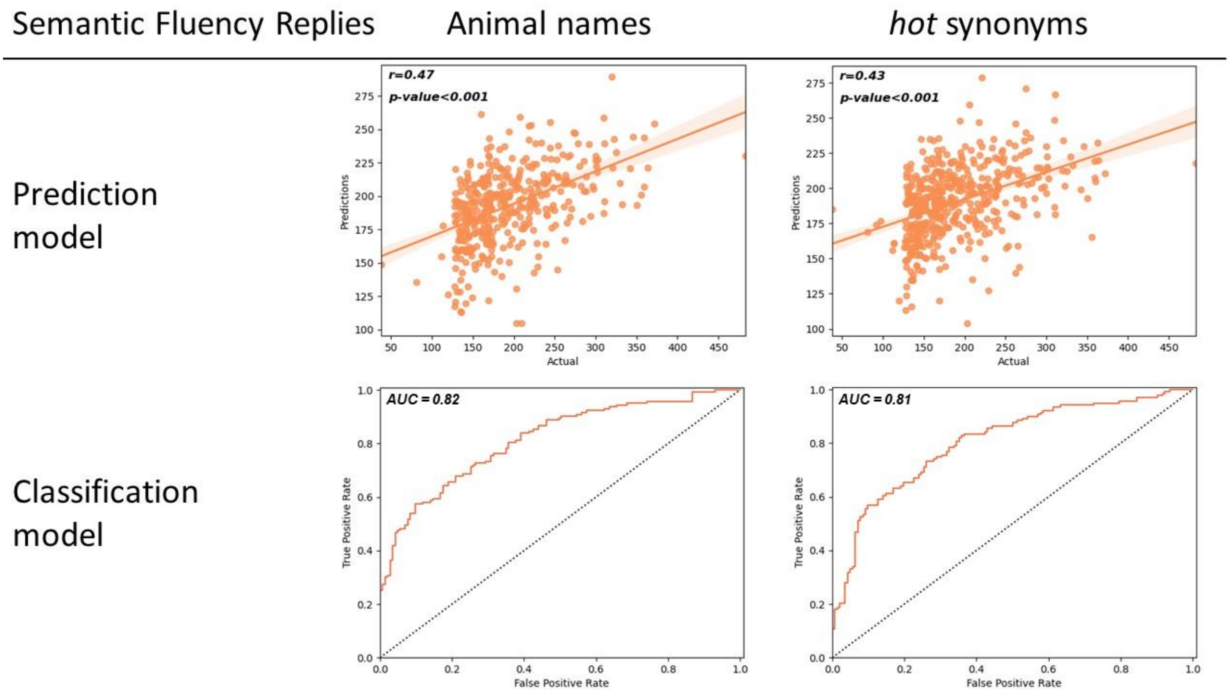
	Variable	N	Pearson's *r*	*p-value*
Animal	Number of Responses	479	0.27	< .001
	Coverage per Response	478	0.13	.004
	Fraction of Responses in LVC	479	-0.15	< .001
	Fraction of LVC Accesses	478	-0.09	.041
	Entropy of LVC Accesses	463	0.13	.003
	Distance from Animal per Response	478	0.16	.001
	Accesses to LVC from Animal	478	-0.09	.039
	Entropy of Access to LVC	479	0.20	< .001
	Norm2	479	-0.12	.009
hot	Number of Responses	479	0.16	< .001
	Fraction of Responses in LVC	479	-0.12	.009
Behavioral	Curiosity	479	0.40	< .001
	Extraversion	479	0.10	.027
	Openness to Experience	479	0.43	< .001
	Conscientiousness	479	-0.09	.045
	Forward Flow	407	0.17	.001
	Intelligence	479	0.11	.015

Machine Learning Analysis

As a next step, we examine the performance of our machine learning model to predict and classify ICAA scores (Figure 8). The prediction model, using a leave one out cross-validation splitting technique and a backwards stepwise linear regression, yielded a significant correlation between the predicted and actual score. When using the multiplex features that were computed with animal category members semantic fluency task replies, prediction results were $r(479) = 0.47$, $MSE = 2454.74$, $p < .001$, features used were Number of Responses, Coverage per Response, Fraction of Responses in LVC, Fraction of LVC Accesses, Entropy of LVC Responses, Max Permanence in LVC, Accesses to LVC from Animal, Fraction of Incorrect Spellings, Curiosity, Agreeableness, Forward Flow. Using the multiplex features that were computed with *hot* synonyms semantic fluency task replies, prediction results were $r(479) = 0.43$, $MSE = 2616.09$, $p < .001$, features used were Number of Responses, Fraction of Responses in LVC, Entropy of LVC Accesses, Max Permanence in LVC, Curiosity, Agreeableness, Conscientiousness, Intelligence. The classification model, using a leave one out cross-validation and a logistic regression classifier with animal names yielded an AUC of .82, using the features Number of Responses, Coverage per Response, Fraction of Responses in LVC, Median Permanence in LVC, Accesses to LVC from Animal, Entropy of Access to LVC, Fraction of Incorrect Spellings, Norm2, Curiosity, Conscientiousness, and with *hot* synonyms yielded an AUC of .81 using the features Number of Responses, Fraction of Responses in LVC, Entropy of LVC Accesses, Max Permanence in LVC, Median Permanence in LVC, Curiosity, Agreeableness, Conscientiousness, Intelligence.

Figure 8

Machine learning model results.



***Note* -** Upper row, Prediction models, shows correlation between predicted (y-axis) and actual (x-axis) ICAA scores. Lower row, Classification model, shows receiver operating characteristics (ROC) curve for the classification of low- and high- ICAA scores. Left, using replies from the Animal names semantic fluency task and other behavioral tasks. Right, using replies from the *hot* synonym semantic fluency task and other behavioral tasks.

Discussion

Experiment 2 aimed to replicate and extend Experiment 1 and findings from Stella & Kenett (2019), with improved prediction and classification of Openness to Experience and with improved prediction and classification of creativity scores. Openness to Experience prediction improved from $r(151) = .31$, MSE = 0.74, $p < .001$ to $r(479) = .69$, MSE = 0.10, $p < .001$ and classification improved from AUC=.75 to AUC=.91, thus showing a much smaller mistake rate in predicting specific Openness to Experience scores, and the ability to differentiate between low- and high- Openness individuals very efficiently. Creativity scores prediction, which was not attempted in Stella & Kenett (2019) was good when ICAA was the dependent variable, showing $r(479) = 0.43$, MSE = 2616.09, $p < .001$. For further perspective, the scale of ICAA scores was between 38 for the lowest scoring participant, and 445 for the highest scoring one, which means the average prediction mistake was 11%. Classification of low- and high- ICAA scores was AUC = .82, extending Stella & Kenett (2019) which showed an AUC of .65.

However, attempting to predict and classify AUT scores was less successful, with prediction of $r(479) = .17$, MSE = 0.002 , $p < .001$, showing an average prediction mistake rate of 17%, and classification of AUC = .62. However, these are still better than chance in classification, and show a small and significant correlation between predicted and actual scores in prediction. These weaker results might have stemmed from the fact that the AUT scores' variance was too small (.002) which made it more difficult for the models to identify the important differences between participants.

Yet, while prediction and classification of AUT scores was weaker than for ICAA and Openness, Stella & Kenett used the Creative Achievement Questionnaire (CAQ; Carson, Peterson & Higgins, 2005) which is similar to the ICAA than to the AUT. Both CAQ and ICAA are self-report creativity questionnaires asking about creative achievements in various domains, while the AUT assesses participants' divergent thinking.

General Discussion

In the current study, I examined how mental navigation through memory (Benigni et al., 2021)—operationalized via a semantic fluency task—predicts complex cognitive behavior. Specifically, the goal of this thesis was to predict Openness to Experience in Experiment 1, and three different dependent variables – Alternative Uses Task (AUT) scores, Inventory of Creative Achievements and Activities (ICAA) scores, both assessing creativity, and Openness to Experience scores – in Experiment 2. To predict these scores, I model the mental lexicon as a cognitive multiplex network that consists of linguistic and conceptual information. I then demonstrate how this multiplex representation relates to differences between low- and high- scores' groups and to individual differences in those measures and can be used to construct a machine learning model that accurately predicts those scores.

This work is based on recent applications of computational methods to study structure and processes in cognitive systems such as language and memory (Baronchelli et al., 2013; Borge-Holthoefer & Arenas, 2010; Günther et al., 2019; Hills & Kenett, 2022; Mandera et al., 2017; Siew et al., 2019). These advances have led to empirical investigation of the structure of memory as graphs, or networks, and the processes operating over them, such as mental navigation (Benigni et al., 2021; Todd & Hills, 2020). However, these studies largely treat different linguistic levels—such as semantics and phonology—separately, and only few studies (Ashby, 2014; Schneider & Newman, 2015; Stella & Kenett, 2019) have examined multidimensional cognitive systems, which represent more than one type of information. These studies deal with analyzing a cognitive multiplex network, which comprises of different layers, or networks, of information. Cognitive multiplex network research has demonstrated how such an approach can be uniquely used to study issues related to language, learning, development, creativity, and clinical research (Castro, 2022;

Castro & Stella, 2019; Levy et al., 2021; Stella, 2019; Stella et al., 2017; Stella et al., 2018; Stella & Kenett, 2019).

Several cognitive multiplex network studies have highlighted the role of a core in the multiplex network that cuts across all of the layers: the largest viable cluster (Stella et al., 2018; Stella & Kenett, 2019). This core, the LVC, is composed of highly general, frequent, and conceptually concrete words which are considered to facilitate language comprehension and processing. Importantly, the LVC emerges from the multiplexity of the mental lexicon and cannot be identified in single-layer modelling approaches. Stella and Kenett (2019) have shown that higher creative individuals retrieve fewer words from the LVC and spend less time searching within it, in line with the idea that higher creative individuals search farther and more broadly through their memory (Kenett, forthcoming; Kenett & Faust, 2019).

Similar to Stella and Kenett (2019), I find several differences in the cognitive multiplex network measures between low- and high- target scores' groups. Specifically, in Experiment 1, I found that the high Openness group generated more synonyms to *hot* and had a smaller fraction of their responses inside the LVC, in addition to generating synonyms that were farther on the network from *hot* than the low Openness group's responses. These findings overlap with Stella and Kenett (2019) who showed that higher creative individuals generate more responses than lower creative individuals, and a smaller fraction of their responses are inside the LVC. The strong relation between Openness and creativity, and the consistency across Experiment 1 and that of Stella and Kenett (2019), highlights and generalizes the use of cognitive multiplex networks to study complex cognitive behavior. Experiment 2 continues to show a reliance on the LVC and the multiplex network features to well predict and classify Creativity and Openness. For example, it shows that the multiplex feature called Fraction of Responses in the LVC is significantly correlated to all the dependent variables and is also significantly different between low- and high- scoring individuals in all the dependent variables. Apart from this example, many more LVC related features are correlated to one or more dependent variable and are different between low- and high- scoring individuals, leaving no doubt about the importance of the LVC in semantic fluency tasks specifically, and more generally in Openness to Experience and creativity. Moreover, in Experiment 2 we can see that Openness to Experience is significantly correlated with both ICAA scores and AUT scores, which makes sense, given what we know from previous research.

Moving beyond group effects, I examined the relation of the cognitive multiplex network measures—based on performance in the *hot* synonym task in Experiment 1 and based on both *hot* synonym and animal names in Experiment 2—and individual differences in Openness and Creativity measures. This analysis revealed multiple significant relations that further highlight the role of the LVC in complex behavior. Similar to the findings of Stella and Kenett (2019), number of responses, fraction of responses in the LVC, coverage of responses, and entropy of responses were significantly related to Openness and Creativity in both Experiments. Thus, this current study replicates the findings of Stella and Kenett (2019), further highlighting the role of the LVC in complex behavior. In addition, it generalizes these findings by also using a different fluency task (both synonyms to *hot* and animal fluency in my study vs. only animal fluency in the Stella and Kenett [2019] study) and a different predicted complex behavior (Openness to Experience and Creativity in my study vs. only creativity in the Stella and Kenett [2019] study). Moreover, the current findings expand previous work (Stella & Kenett, 2019), by moving from between-group comparisons to demonstrating how this analysis can capture individual differences.

Notably, the supervised machine learning model results show a small to medium correlation between predicted and actual Openness scores in Experiment 1 and improves significantly in Experiment 2. Moreover, while classification ability in Experiment 1 was close but did not reach the benchmark for clinical use, which is .80 (Jones & Athanasiou, 2005), in Experiment 2 both Openness scores and ICAA scores classification passed this benchmark, whether we used the animal names replies or the *hot* synonyms replies. These results highlight the ability to quantitatively predict Openness and creativity scores simply based on how participants retrieve synonyms or generate members of a certain category.

The results provide further support that the mental lexicon can be modelled using multiplex networks, and that the characteristics of such a model are linked to complex cognitive traits, such as language, development, and creativity, in typical and clinical populations (Levy et al., 2021; Stella, 2019, 2020; Stella et al., 2017; Stella & Kenett, 2019). Furthermore, the link outlined here between the LVC and complex behavior indicates that multiplexity is an important feature of mental representations of linguistic knowledge. Since the LVC emerges from the multiplex interplay of semantic and phonological associations, the current work implies that cognitive multiplex networks represent a natural and convenient framework for exploring cognitive capacities, through quantitative and reproducible measurements, free from the constraints of subjective evaluations (e.g., self-report scales).

More generally, these findings provide further support for the link of personality traits (Openness to Experience), creativity, and the mental lexicon. Traditionally, cognition and personality have been investigated separately, but a large body of work has linked creativity with Openness, a personality trait that has been referred to as the “creativity trait” (Christensen, Cotter, et al., 2018; Christensen, Kenett, et al., 2018; Kaufman et al., 2016; Oleynick et al., 2017). Christensen, Kenett et al. (2018) have recently shown a relation between semantic memory structure and Openness. The authors show how people high on Openness had a more flexible, richly connected semantic memory network (Christensen, Kenett, et al., 2018). Our study provides further evidence supporting the relation between Openness and the mental lexicon, pushing these two domains closer together. Thus, increased theoretical focus on the role of the mental lexicon in personality—and especially in Openness to Experience—is needed. Recent studies have begun theoretically studying personality as a complex dynamic system using network science methodology (Beck & Jackson, 2021). Based on our current study, future cognitive multiplex network research should expand to incorporate a "personality" layer to more directly study how cognition and personality impact each other and interact together to realize complex human behavior.

Notably, not all the results of this thesis were satisfying. Specifically, classification and prediction of AUT scores in Experiment 2 were lower than expected. Although it is hard to state for certain what led to such weaker success, it is likely due to the variance in participants' AUT scores was very small. Machine learning models learns which features and measures to use in prediction and classification based on the variance between participants, therefore it might not be surprising that the models were not able to provide a very good prediction for AUT scores. Since AUT is a well-established and acceptable task, it seems unlikely that variance between participants would be very small. Therefore, using the MAD tool to compute AUT scores might not ideal to use it when attempting to predict and classify AUT scores. Another important limitation of this study is that the scores that were well-predicted were both the scores based on self-report measures. It might mean that the predicted variables include a component of self-report instead of measuring only the target traits. This doesn't make the results un-trustworthy, but it does make it important to replicate with an objective, non-self-report measure, in order to strengthen the construct validity of this thesis.

Apart from replicating this thesis with non-self-report dependent variables, another future step in this line of work should be to try and use the methods used here to study other complex cognitive traits. Showing evidence of relation between the mental lexicon and other cognitive traits would broaden the scope of findings shown in this thesis and widen the variety of objective measures to study cognition. Moreover, using a shorter semantic fluency task, of 30 seconds for example, in order to compute Multiplex Network measures, could also be an interesting step forward, because it would make this method even more practical and applicative for the world outside of academia.

In summary, the results of the current study demonstrate that it is possible to predict and classify Openness and creativity scores using multiplex networks and a very short task, even when data size is limited, which improves when data size is more suitable for machine learning tasks. Therefore, this work adds further demonstrate how such computational tools can be used to predict complex cognitive capacities. Furthermore, my study demonstrates the ability to predict complex behavior from simple, behavioral tasks such as semantic fluency. These findings push personality and cognition closer together and provide initial evidence for the ability to develop automatic, objective scoring of Openness and of Creativity. Such a quantitative direction has largely advanced creativity research over the past decade (Beaty & Johnson, 2021; Beaty et al., 2018; Dumas et al., 2021; Ovando-Tellez et al., 2022). Given that Openness and Creativity are so closely related, such quantitative methods should be further applied to advance Openness-and personality more generally— and Creativity research.

References

Abbott, J. T., Austerweil, J. L., & Griffiths, T. L. (2015). Random walks on semantic networks can resemble optimal foraging. *Psychological Review*, *122*(3), 558–569. https://doi.org/10.1037/A0038693

Acar, S., & Runco, M. A. (2019). Divergent thinking: New methods, recent research, and extended theory. *Psychology of Aesthetics, Creativity, and the Arts*, *13*(2), 153–158. https://doi.org/10.1037/ACA0000231

Alpaydin, E. (2020). Introduction to machine learning. MIT press.

Ardila, A., Ostrosky-Solís, F., & Bernal, B. (2007). Cognitive testing toward the future: The example of semantic verbal Fluency (ANIMALS). *Wiley-Blackwell*, *41*(5), 324–332. https://doi.org/10.1080/00207590500345542

Ashby, F. G. (2014). Multidimensional models of perception and cognition. Psychology Press.

Baronchelli, A., Ferrer-i-Cancho, R., Pastor-Satorras, R., Chater, N., & Christiansen, M. H. (2013). Networks in cognitive science. Trends in Cognitive Sciences, 17(7), 348-360. https://doi.org/10.1016/j.tics.2013.04.010

Beaty, R. E., & Johnson, D. R. (2021). Automating creativity assessment with SemDis: An open platform for computing semantic distance. Behavior Research Methods, 53(2), 757-780. https://doi.org/10.3758/s13428-020-01453-w

Beaty, R. E., Kenett, Y. N., Christensen, A. P., Rosenberg, M. D., Benedek, M., Chen, Q., Fink, A., Qiu, J., Kwapil, T. R., Kane, M. J., & Silvia, P. J. (2018). Robust prediction of individual creative ability from brain functional connectivity. *Proceedings of the National Academy of Sciences*, *115*(5), 1087–1092. https://doi.org/10.1073/PNAS.1713532115

Beaty, R. E., & Silvia, P. J. (2012). Why do ideas get more creative across time? An executive interpretation of the serial order effect in divergent thinking tasks. *Psychology of Aesthetics, Creativity, and the Arts, 6*(4), 309–319. https://doi.org/10.1037/a0029171

Beaty, R. E., Silvia, P. J., Nusbaum, E. C., Jauk, E., & Benedek, M. (2014). The roles of associative and executive processes in creative cognition. Memory & cognition, 42(7), 1186-1197.

Beaty, R. E., Zeitlen, D. C., Baker, B. S., & Kenett, Y. N. (2021). Forward flow and creative thought: Assessing associative cognition and its role in divergent thinking. Thinking Skills and Creativity, 41, 100859.

Beck, E. D., & Jackson, J. J. (2021). Network approaches to representing and understanding personality dynamics. In D. Wood, S. J. Read, P. D. Harms, & A. Slaughter (Eds.), Measuring and Modeling Persons and Situations (pp. 465-497). Academic Press.

Benedek, M., & Neubauer, A. C. (2013). Revisiting Mednick's model on creativity-related differences in associative hierarchies. Evidence for a common path to uncommon thought. *The Journal of Creative Behavior*, *47*(4), 273–289. https://doi.org/10.1002/JOCB.35

Benigni, B., Dallabona, M., Bravi, E., Merler, S., & De Domenico, M. (2021). Navigating concepts in the human mind unravels the latent geometry of Its semantic space. Complexity, 2021, 6398407. https://doi.org/10.1155/2021/6398407

Borge-Holthoefer, J., & Arenas, A. (2010). Semantic Networks: Structure and Dynamics. *Entropy 2010, Vol. 12, Pages 1264-1302*, *12*(5), 1264–1302. https://doi.org/10.3390/E12051264

Carson, S. H., Peterson, J. B., & Higgins, D. M. (2005). Reliability, validity, and factor structure of the creative achievement questionnaire. Creativity research journal, 17(1), 37-50.

Castro, N. (2022). Methodological considerations for incorporating clinical data Into a network model of retrieval failures. Topics in Cognitive Science, 14(1), 111-126. https://doi.org/https://doi.org/10.1111/tops.12531

Castro, N., & Siew, C. S. (2020). Contributions of Modern Network Science to the Cognitive Sciences: Revisiting research spirals of representation and process. Proceedings of the Royal Society A, 476(2238), 20190825.

Castro, N., & Stella, M. (2019). The multiplex structure of the mental lexicon influences picture naming in people with aphasia. Journal of Complex Networks, 7(6), 913-931.

Cattell, R. B., & Cattell, A. K. S. (1960). Measuring intelligence with the culture fair tests. Institute for Personality and Ability Testing.

Christensen, A. P., Cotter, K. N., & Silvia, P. J. (2019). Reopening openness to experience: A network analysis of four openness to experience inventories. Journal of Personality Assessment, 101(6), 574-588.

Christensen, A. P., & Kenett, Y. N. (2021). Semantic network analysis (SemNA): A tutorial on preprocessing, estimating, and analyzing semantic networks. Psychological Methods, No Pagination Specified-No Pagination Specified. https://doi.org/10.1037/met0000463

Christensen, A. P., Kenett, Y. N., Cotter, K. N., Beaty, R. E., & Silvia, P. J. (2018). Remotely close associations: Openness to experience and semantic memory structure. European Journal of Personality, 32(4), 480-492.

Collins, R. P., Litman, J. A., & Spielberger, C. D. (2004). The measurement of perceptual curiosity. Personality and individual differences, 36(5), 1127-1141.

Dai, W., Brisimi, T. S., Adams, W. G., Mela, T., Saligrama, V., & Paschalidis, I. C. (2015). Prediction of hospitalization due to heart diseases by supervised learning methods. *International Journal of Medical Informatics, 84*(3), 189–197. https://doi.org/10.1016/J.IJMEDINF.2014.10.002

De Deyne, S., Navarro, D. J., Perfors, A., Brysbaert, M., & Storms, G. (2018). The “Small World of Words” English word association norms for over 12,000 cue words. *Behavior Research Methods*, *51*(3), 987–1006. https://doi.org/10.3758/S13428-018-1115-7

Diedrich, J., Jauk, E., Silvia, P. J., Gredlein, J. M., Neubauer, A. C., & Benedek, M. (2018). Assessment of real-life creativity: The Inventory of Creative Activities and Achievements (ICAA). Psychology of Aesthetics, Creativity, and the Arts, 12(3), 304.

Dumas, D., Organisciak, P., & Doherty, M. (2021). Measuring originality with human raters and text-mining models: A psychometric comparison of methods. Psychology of Aesthetics, Creativity and the Arts, 15(4), 645-663. https://doi.org/https://doi.org/10.1037/aca0000319 Ekstrom, R. B., Dermen, D., & Harman, H. H. (1976). Manual for kit of factor-referenced cognitive tests. Educational Testing Service.

Frith, E., Kane, M. J., Welhaf, M. S., Christensen, A. P., Silvia, P. J., & Beaty, R. E. (2021). Keeping creativity under control: Contributions of attention control and fluid intelligence to divergent thinking. *Creativity Research Journal*. https://doi.org/10.1080/10400419.2020.1855906

Günther, F., Rinaldi, L., & Marelli, M. (2019). Vector-space models of semantic representation from a cognitive perspective: A discussion of common misconceptions. Perspectives on Psychological Science, 14(6), 1006-1033.

Hills, T. T., Jones, M. N., & Todd, P. M. (2012). Optimal foraging in semantic memory. *Psychological Review*, *119*(2), 431. https://doi.org/10.1037/A0027373

Hills, T. T., Todd, P. M., & Jones, M. N. (2015). Foraging in Semantic Fields: How we search through memory. *Topics in Cognitive Science*, *7*(3), 513–534. https://doi.org/10.1111/TOPS.12151

Hills, T. T., & Kenett, Y. N. (2022). Is the Mind a Network? Maps, Vehicles, and Skyhooks in Cognitive Network Science. Topics in Cognitive Science, 14(1), 189-208. https://doi.org/https://doi.org/10.1111/tops.12570

Jones, C. M., & Athanasiou, T. (2005). Summary receiver operating characteristic curve analysis techniques in the evaluation of diagnostic tests. The Annals of thoracic surgery, 79(1), 16-20.

Karuza, E. A., Thompson-Schill, S. L., & Bassett, D. S. (2016). Local patterns to global architectures: Influences of network topology on human learning. Trends in Cognitive Sciences, 20(8), 629-640. https://doi.org/10.1016/j.tics.2016.06.003

Kashdan, T. B., Disabato, D. J., Goodman, F. R., & McKnight, P. E. (2020). The Five-Dimensional Curiosity Scale Revised (5DCR): Briefer subscales while separating overt and covert social curiosity. Personality and Individual Differences, 157, 109836.

Kaufman, S. B., Quilty, L. C., Grazioplene, R. G., Hirsh, J. B., Gray, J. R., Peterson, J. B., & DeYoung, C. G. (2016). Openness to experience and intellect differentially predict creative achievement in the arts and sciences. Journal of Personality, 84(2), 248-258.

Kenett, Y. N. (2018). Going the extra creative mile: The role of semantic distance in creativity - Theory, research, and measurement. *The Cambridge Handbook of the*

Neuroscience of Creativity, (pp. 233–248). https://doi.org/10.1017/9781316556238.014

Kenett, Y. N., Beaty, R. E., Silvia, P. J., Anaki, D., & Faust, M. (2016). Structure and flexibility: Investigating the relation between the structure of the mental lexicon, fluid intelligence, and creative achievement. *Psychology of Aesthetics, Creativity, and the Arts, 10*(4), 377–388. https://doi.org/10.1037/aca0000056

Kenett, Y. N., & Faust, M. (2019). A semantic network cartography of the creative mind. *Trends in Cognitive Sciences*, *23*(4), 271–274. https://doi.org/10.1016/j.tics.2019.01.007

Kenett, Y. N. (forthcoming). Creatively searching through semantic memory structure: A short integrative revie. In L. J. Ball & F. Vallée-Tourangea (Eds.), Routledge International Handbook of Creative Cognition.

Kenett, Y. N., & Hills, T. T. (2022). Editors' introduction to networks of the mind: How can network science elucidate our understanding of cognition? [https://doi.org/10.1111/tops.12598]. Topics in Cognitive Science, 14(1), 45-53. https://doi.org/https://doi.org/10.1111/tops.12598

Lee, K., & Ashton, M. C. (2010). Psychometric properties of the HEXACO personality inventory. *Http://Dx.Doi.Org/10.1207/S15327906mbr3902_8*, *39*(2 SPEC. ISS.), 329–358. https://doi.org/10.1207/S15327906MBR3902_8

Lin, Y., Zhou, K., & Li, J. (2018). Prediction of slope stability using four supervised learning methods. *IEEE Access*, *6*, 31169–31179. https://doi.org/10.1109/ACCESS.2018.2843787

Litman, J. A. (2008). Interest and deprivation factors of epistemic curiosity. Personality and individual differences, 44(7), 1585-1595.

Litman, J. A., & Jimerson, T. L. (2004). The measurement of curiosity as a feeling of deprivation. Journal of personality assessment, 82(2), 147-157.

Litman, J. A., & Spielberger, C. D. (2003). Measuring epistemic curiosity and its diversive and specific components. Journal of personality assessment, 80(1), 75-86.

Levy, O., Kenett, Y. N., Oxenberg, O., Castro, N., De Deyne, S., Vitevitch, M. S., & Havlin, S. (2021). Unveiling the nature of interaction between semantics and phonology in lexical access based on multilayer networks. Scientific Reports, 11(1), 14479. https://doi.org/10.1038/s41598-021-93925-y

Mandera, P., Keuleers, E., & Brysbaert, M. (2017). Explaining human performance in psycholinguistic tasks with models of semantic similarity based on prediction and counting: A review and empirical validation. Journal of Memory and Language, 92, 57-78. https://doi.org/http://dx.doi.org/10.1016/j.jml.2016.04.001

McCrae, R. R., Paul T.   Costa, J., & Martin, T. A. (2010). The NEO–PI–3: A more readable revised NEO personality inventory. *Http://Dx.Doi.Org/10.1207/S15327752jpa8403_05*, *84*(3), 261–270. https://doi.org/10.1207/S15327752JPA8403_05

Mednick, S. (1962). The associative basis of the creative process. *Psychological Review*, *69*(3), 220–232. https://doi.org/10.1037/H0048850

Miller, G. A. (1995). WordNet: *Communications of the ACM*, *38*(11), 39–41. https://doi.org/10.1145/219717.219748

Oleynick, V. C., DeYoung, C. G., Hyde, E., Kaufman, S. B., Beaty, R. E., & Silvia, P. J. (2017). Openness/Intellect: The core of the creative personality. In G. J. Fiest, R. Reiter-Palmon, & J. C. Kaufman (Eds.), Cambridge handbook of creativity and personality research (pp. 9-27). Cambridge University Press.

Ovando-Tellez, M., Kenett, Y. N., Benedek, M., Bernard, M., Belo, J., Beranger, B., Bieth, T., & Volle, E. (2022). Brain connectivity–based prediction of real-life creativity is mediated by semantic memory structure. Science Advances, 8(5), eabl4294. https://doi.org/10.1126/sciadv.abl4294

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. Journal of Statistical Software, 48, 1-36.

Runco, M. A., & Jaeger, G. J. (2012). The standard definition of creativity. Creativity research journal, 24(1), 92-96.

Schneider, W. J., & Newman, D. A. (2015). Intelligence is multidimensional: Theoretical review and implications of specific cognitive abilities. Human Resource Management Review, 25(1), 12-27.

Siew, C. S. Q., Wulff, D. U., Beckage, N. M., & Kenett, Y. N. (2019). Cognitive network science: A review of research on cognition through the lens of network representations, processes, and dynamics. Complexity, 2019, 2108423. https://doi.org/10.1155/2019/2108423

Silvia, P. J., Wigert, B., Reiter-Palmon, R., & Kaufman, J. C. (2012). Assessing creativity with self-report scales: A review and empirical evaluation. *Psychology of Aesthetics, Creativity, and the Arts*, *6*(1), 19–34. https://doi.org/10.1037/A0024071

Stella, M. (2018). Cohort and rhyme priming emerge from the multiplex network structure of the mental lexicon. *Complexity*, *2018*. https://doi.org/10.1155/2018/6438702

Stella, M., Beckage, N. M., Brede, M., & De Domenico, M. (2018). Multiplex model of mental lexicon reveals explosive learning in humans. *Scientific Reports*, *8*(1), 1–11. https://doi.org/10.1038/s41598-018-20730-5

Stella, M., & Kenett, Y. N. (2019). Viability in multiplex lexical networks and machine learning characterizes human creativity. *Big Data and Cognitive Computing*, *3*(3), 1–19. https://doi.org/10.3390/bdcc3030045

Stella, M. (2019). Modelling early word acquisition through multiplex lexical networks and machine learning. Big Data and Cognitive Computing, 3(1), 10.

Stella, M. (2020). Multiplex networks quantify robustness of the mental lexicon to catastrophic concept failures, aphasic degradation and ageing. Physica A: Statistical Mechanics and its Applications, 554, 124382. https://doi.org/https://doi.org/10.1016/j.physa.2020.124382

Stella, M., Beckage, N. M., & Brede, M. (2017). Multiplex lexical networks reveal patterns in early word acquisition in children [Article]. Scientific Reports, 7, 46730. https://doi.org/10.1038/srep46730 Thurstone, L. L. (1938). *Primary mental abilities*. University of Chicago Press.

Todd, P. M., & Hills, T. T. (2020). Foraging in Mind. Current Directions in Psychological Science, 29(3), 309-315. https://doi.org/10.1177/0963721420915861

Volle, E. (2018). Associative and controlled cognition in divergent thinking: Theoretical, experimental, neuroimaging evidence, and new directions. In R. E. Jung & O. Vartanian (Eds.), *The Cambridge handbook of the neuroscience of* *creativity* (pp. 333–360). Cambridge, UK: Cambridge University Press. https://doi.org/10.1017/9781316556238.020

Yu, Y., Beaty, R., Forthmann, B., Beeman, M., Cruz, J. H., & Johnson, D. R. (2022). A mad method to assess idea novelty: Improving validity of automatic scoring using maximum associative distance (MAD).

ניבוי ותיוג של תכונות קוגניטיביות ופסיכולוגיות באמצעות רשתות רב שכבתיות

חיבור על מחקר

לשם מילוי חלקי של הדרישות לקבלת התואר

מגיסטר למדעים במדעי ההתנהגות והניהול – פסיכולוגיה קוגניטיבית והנדסת גורמי אנוש

גל סמואל

הוגש לסנט הטכניון – מכון טכנולוגי לישראל

אלול, התשפ"ב, חיפה, ספטמבר 2022

המחקר התבצע בהנחיית

ד"ר יועד קנת

בפקולטה להנדסת תעשייה וניהול

אני מודה לטכניון על התמיכה הכספית הנדיבה בהשתלמותי

תקציר

יצירתיות היא מושג רב-מימדי מורכב, המכיל בתוכו תהליכים קוגניטיביים שונים, ועל כן, מהווה מושג שקשה לחקור אותו. חשיבה יצירתית מסייעת לנו לזהות ולפתור בעיות ולהיות חדשניים, לכן ישנה חשיבות גדולה עבור החברה בה אנו חיים ללמוד היטב את מאפייניה של תכונה זו. בשנים האחרונות חלה פריצת דרך בחקר היצירתיות, בעקבות החדירה של כלים ומודלים חישוביים שמאפשרים מדידה כמותית ואובייקטיבית של תופעה זו. כלים אלה מאפשרים לחקור את התפקיד של זיכרון סמנטי—המערכת הקוגניטיבית האוגרת ידע—בהבדלים בין אישיים ביצירתיות. בפרט, השימוש בכלים מתורת הגרפים מאפשר לייצג זיכרון סמנטי כרשת סמנטית, ולחקור את המאפיינים הכמותיים של רשתות אלה ביחס ליחידים או קבוצות בהקשר של ההבדלים ביניהם ביכולת יצירתית.

מחקר היצירתיות מראה שרשתות סמנטיות הן רכיב חשוב של יצירתיות, מכיוון שהן מאפשרות חיבור בין מושגים מרוחקים, המאפשר בתורו יצירה של רעיונות חדשים ומקוריים. עם זאת, נעשו מעט מאוד נסיונות לחקור מבני ידע מורכבים, רב-מימדיים, ואת הקשר של אותם מבנים ליצירתיות. בחיבור זה, השתמשתי בשיטות חישוביות מתקדמות ממדעי הרשתות כדי לייצר ייצוג רב-מימדי של ה"לקסיקון המנטלי" ובחנתי את הדרך שבה אנשים מחפשים בו במהלך מטלת חיפוש מנטלי, על מנת לנבא את ציוניהם במדדי יצירתיות ופתיחות לחוויות (תכונת האישיות Openness to Experience). עשיתי זאת בעזרת ניתוח רשת רב-מימדית, אשר מאפשרת למדל מערכות מורכבות לכדי גרף רב-מימדי. רשת זו מורכבת משכבה סמנטית, פונולוגית, אסוציאטיבית ושכבה של קשרי כללי/פרטי (hypernym/hyponym) ובאמצעות כך מהווה מודל המכיל בתוכו מידע מכל אותם סוגים עבור מושגים שונים. כך, היא מייצגת את ה"לקסיקון המנטלי" על רבדיו השונים.

בשני ניסויים שערכתי בחנתי כיצד מאפייני החיפוש המנטלי בזיכרון של נבדקים על גבי רשת הלקסיקון הרב-מימדי מבחינה ומסווגת בין אנשים ביחס לציוני היצירתיות והפתיחות שלהם. התוצאות משני הניסויים המופיעים פה מראות שקיימים הבדלים בינאישיים בדרך שבה אנשים מנווטים בלקסיקון המנטלי הרב-מימדי שלהם. למשל, ניתן לראות כי השימוש של אנשים יצירתיים ופתוחים לחוויות במילים נפוצות שונה מהשימוש של אנשים פחות יצירתיים ופחות פתוחים לחוויות (עפ"י ציוניהם במדדים המשקפים יצירתיות ופתיחות לחוויות). הבדלים אלה מסייעים לנבא ציוני יצירתיות ופתיחות לחוויות. תוצאות הניסויים בחיבור זה תומכות בהשערה כי ניתן לנבא ציוני פתיחות לחוויות ויצירתיות ולתייג בהצלחה

נבדקים נמוכים וגבוהים בתכונות אלה באמצעות כלים חישוביים ובאמצעות מאפייני הניווט של הנבדקים ברשת הרב-שכבתית המייצגת את ה"לקסיקון המנטלי".

בניסוי מספר 1 נמצא דיוק של 75% בתיוג נבדקים כנמוך או גבוה בפתיחות לחוויות. בניסוי 2 אף נראה שיפור לרמת דיוק של 91%, ואף בוצע ניבוי של ציוני פתיחות לחוויות שהראה $r(479)$ = .69, MSE = 0.1, $p < .001$ בין הציונים המנובאים לציונים האמיתיים. ניסוי 2 כלל גם ניבוי ותיוג של ציוני יצירתיות משני מבחנים שונים. האחד, נמדד באמצעות שאלון דיווח-עצמי (ICAA) והשני נמדד באמצעות מטלת חשיבה מתבזרת (AUT). התוצאות הטובות ביותר לניבוי ותיוג ICAA הראו דיוק של 82% בתיוג של נמוכים וגבוהים במדד זה, וניבוי של $r(479)$ = 0.47, MSE = 2454.74 , $p < .001$ בין הציונים המנובאים לציונים האמיתיים. התוצאות הטובות ביותר לניבוי ותיוג של AUT הראו דיוק של 62% בתיוג של נמוכים וגבוהים במדד זה, וניבוי של $r(479)$ = .17, MSE = 0.002 , $p < .001$ בין הציונים המנובאים לציונים האמיתיים. אף על פי שתוצאות התיוג והניבוי של AUT היו נמוכות ביחס לפתיחות לחוויות ולICAA, עדיין מדובר בתיוג שהוא טוב יותר מניחוש (כלומר, מעל 50%) ועדיין קיים מתאם משמעותי ומובהק בין הציונים המנובאים לציונים האמיתיים. לסיכום, אוסף התוצאות של ניסויים 1 ו2 מספק הוכחה מרגשת לאפשרות להשתמש בכלים חישוביים כמו רשתות רב-שכבתיות, כדי לחקור ולנבא תכונות קוגניטיביות מורכבות.